

yang_seonhyeHW7

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Question 1

The assumptions of the Gauss-Markov theorem are:

$$\begin{aligned}GM_1 : E(\epsilon) &= 0 \\ GM_2 : \text{var}(\epsilon) &= \theta^2 I\end{aligned}$$

Question 2

In order to show that the $\hat{\beta}$ is unbiased we would want the following result:

$$\begin{aligned}E[\hat{\beta}] &= \beta \\ \hat{\beta} &= (X^T X)^{-1} X^T y \\ E[(X^T X)^{-1} X^T y]\end{aligned}$$

$$(X^T X)^{-1} X^T$$

is a constant therefore we can take it out and it becomes

$$(X^T X)^{-1} X^T E[y]$$

$$\begin{aligned}E[y] &= X\beta \\ (X^T X)^{-1} X^T X\beta \\ (X^T X)^{-1} X^T X\end{aligned}$$

is an identity matrix I Therefore,

$$E[\hat{\beta}] = \beta$$

Question 3

In order to show that \hat{y} is an unbiased estimator of $E[y]$, recall that $\hat{y} = X\hat{\beta}$

$$\begin{aligned}E(\hat{y}) &= y \\ E(\hat{y}) &= E(X\hat{\beta}) \\ E(\hat{y}) &= XE(\hat{\beta}) \\ X(X^T X)^{-1} X^T E[y]\end{aligned}$$

$$X(X^T X)^{-1} X^T$$

is an identity matrix I

$$E[y] = X\beta$$

$$y = X\beta$$

Therefore, $E(\hat{y}) = y$ and \hat{y} is an unbiased estimator of $E[y]$

Question 4

We know that $b_1 = \frac{y_2 - y_1}{x_2 - x_1}$. We also know that (x_1, y_1) and (x_2, y_2) are the first two points of our dataset, When we set out to show that $E(b_1) = \beta_1$, we first find $E(b_1)$:

$$\begin{aligned} E(b_1) &= E\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \\ E(b_1) &= E\left(\frac{\beta_0 + \beta_1 x_2 + \epsilon_2 - \beta_0 - \beta_1 x_1 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= E\left(\frac{\beta_1 x_2 + \epsilon_2 - \beta_1 x_1 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= E\left(\frac{\beta_1(x_2 - x_1) + \epsilon_2 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= E\left(\frac{\beta_1(x_2 - x_1)}{x_2 - x_1}\right) + E\left(\frac{\epsilon_2 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= E(\beta_1) + E\left(\frac{\epsilon_2 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= \beta_1 + E\left(\frac{\epsilon_2 - \epsilon_1}{x_2 - x_1}\right) \\ E(b_1) &= \beta_1 + \frac{E(\epsilon_2) - E(\epsilon_1)}{x_2 - x_1} \\ E(b_1) &= \beta_1 + \frac{0}{x_2 - x_1} \\ E(b_1) &= \beta_1 \end{aligned}$$

Thus $E(b_1) = \beta_1$.

Question 5

We know that b_1 :

$$\begin{aligned} b_1 &= \frac{y_2 - y_1}{x_2 - x_1} \\ b_1 &= \frac{\beta_0 + \beta_1 x_2 + \epsilon_2 - \beta_0 - \beta_1 x_1 - \epsilon_1}{x_2 - x_1} \\ b_1 &= \frac{\beta_1 x_2 + \epsilon_2 - \beta_1 x_1 - \epsilon_1}{x_2 - x_1} \\ b_1 &= \frac{\beta_1(x_2 - x_1) + \epsilon_2 - \epsilon_1}{x_2 - x_1} \end{aligned}$$

And knowing that $var(a\mathbf{X}) = a^2 var(\mathbf{X})$:

$$var(b_1) = var\left(\frac{\beta_1(x_2 - x_1)}{x_2 - x_1}\right) + var\left(\frac{\epsilon_2 - \epsilon_1}{x_2 - x_1}\right)$$

$$var(b_1) = 0 + var\left(\frac{\epsilon_2 - \epsilon_1}{x_2 - x_1}\right)$$

$$var(b_1) = \frac{var(\epsilon_2) + var(\epsilon_1)}{(x_2 - x_1)^2}$$

Also knowing that $var(\epsilon) = \sigma^2$:

$$var(b_1) = \frac{2\sigma^2}{(x_2 - x_1)^2}$$